Rapid detection of agricultural food crop contamination via hyperspectral remote sensing

Terrance West[1], *Student Member, IEEE*, Saurabh Prasad[1], *Member, IEEE*, Lori Mann Bruce[1]*, *Senior Member, IEEE*, Daniel Reynolds[2]

[1]Electrical and Computer Engineering Department, [2]Plant and Soil Science Department
Mississippi State University, Mississippi State, MS, 39762, USA
* *bruce@bagley.msstate.edu*

Passive optical remote sensing techniques, including hyperspectral imaging, have been used in many different applications in agriculture, from detecting weeds to characterizing crop stresses to estimating crop yields. Many factors have been shown to affect the optical reflectance properties of crops, including water content, diseases, and soil nutrients. For example, MacNeil et al. used diffuse reflectance spectroscopy to differentiate between injury caused by the white apple leafhopper (*Typhlocyba pomaria*) and nitrogen deficiency on apple (*Malus sylvestris*) leaves [1]. Research in remote sensing would indicate the possibility of detecting pesticides spray drift onto susceptible crops. Adcock et al. found that paraquat injury on soybeans (*Glycine max*) was detected using a radiometer at 800nm [2]. Mortimer et al. found that spectroradiometer readings correctly classified sublethal doses of glyphosate on non-transgenic cotton when using a linear discriminatory analysis, even when injury was not detected visually [3].

Thus, multispectral and hyperspectral imagers are powerful tools in remote sensing and provide great promise for rapid detection and characterization of agricultural food crop contaminants. Hyperspectral imagers can be useful in detecting when a contaminant has been introduced to an agricultural crop before the crop stresses are visible to the human eye, providing a valuable lead time in first response. In some cases there is no visible indicator that the contaminant has been introduced to the vegetation; i.e. the optical reflectance is altered only in the non-visible regions of the optical spectrum. A hyperspectral image can provide densely sampled reflectance measurements across the visible and near infrared regions of the spectrum, resulting in hyperspectral signatures with 100's of spectral bands. These signatures can then be analyzed with advanced mathematical algorithms, to determine if a particular target is present. In this application, the "target" would be "a contaminated agricultural crop" and the "nontarget" would be "an agricultural crop under normal conditions".

These subtle targets can prove quite difficult to recognize and thus require the use of more sophisticated spectral features, necessitating the use of hyperspectral sensors. However, the high dimensionality of hyperspectral data requires one to have a large number of training samples for designing automated target recognition (ATR) systems. A common problem in many real-world applications is the lack of sufficient training data. The need for larger amounts of training data stems from the fact that the number of training samples required is directly related to the dimensionality of the classifier [4]. In order to avoid this problem, the hyperspectral datasets must be preprocessed, thereby reducing the dimensionality to an acceptable level.

This paper investigates the use of discrete wavelet transforms, multi-classifiers, and decision fusion in an ATR system to address the challenges of hyperspectral data as it relates to food crop contamination detection [5, 6, 7, 8]. The first stage of the ATR system employs a discrete wavelet transforms of the hyperspectral data. The second stage of the system is dimensionality reduction, which involves the selection and partitioning of wavelet coefficients. The third stage of the system is classification. This stage involves the classification of each subset of features by an individual classifiers. The fourth stage of the system is decision fusion. This involves fusing the decisions from stage three to form one label (i.e. "target" or "nontarget" as well as a measure of label confidence). The performance of the proposed system is compared to ATR methods currently used in the remote sensing community, including those based on principal component analysis (PCA), discriminant analysis feature extraction (DAFE), and maximum-likelihood classifiers [4].

This paper presents the results of experimental analyses to determine quantitative accuracies of the proposed ATR system. The authors conducted field-level experiments to determine the ATR system's efficacy at detecting chemical contaminations of wheat and corn. Surrogate chemicals were used, including glyphosate, paraquat, and pyrithiobac. The corn and wheat was planted in 96.5 cm rows in 3.86m by 12.2 m plots at a seeding rate of 108,000 seed/ha. The treatments were arranged as 2-factor factorial in a randomized complete block design. Factor A consist of the herbicides: glyphosate, glufosinate, paraquat, and pyrithiobac. Factor B consist of the herbicide rate: 200, 100, 50, 25, 12, 6, 3, and 2 % of the labeled rate for each herbicide evaluated. Additionally, the authors collected hyperspectral measurements of soybean crops contaminated with a biological pathogen, namely Asian soybean rust, and under control conditions. For both the chemical and biological contaminants, hyperspectral data were collected with both handheld spectrometers (e.g. ASD units [9]) and airborne imagers (e.g. SpecTIR system [10]). The experimental results are very promising, resulting in accuracies as high as 90+% for some cases, and demonstrate the efficacy of the proposed system for rapid detection of agricultural food crop contaminations.

References

1. J. D. Macneil, M. Hikichi, R. S. Downing, "An Investigation of the Effects of Seasonal Changes, Leaf Maturity, Nitrogen Deficiency and Leafhopper Injury on the Chlorophyll Content and Diffuse Reflectance Spectroscopic Properties of Orchard Leaves", International Journal of Environmental Analytical Chemistry, vol. 31, no. 1, Nov. 1987, pp 55 – 62.
2. T. E. Adcock, F. W. Nutter, P. A. Banks, "Measuring herbicide injury to soybeans (Glycine max) using a radiometer", Weed Science , vol. 38, no. 6, Nov. 1990, pp. 625 – 627.
3. M. L. Mortimer, J. H. Massey, D. R. Shaw, J. R. Steil, J. A. Ballweber, and M.C. Smith, "Employing Remote Sensing to Evaluate Changes in Land Use and Estimate Probable Pesticide Runoff to Surface Waters" , Proceedings of Southern Weed Science Society, vol. 54, 2001
4. R.O. Duda, P.E. Stark, D.G. Stork, *Pattern Classification*, Wiley Inter-science, October 2000.
5. S. Prasad, L.M. Bruce, "Decision Fusion with Confidence based Weight Assignment for Hyperspectral Target Recognition," in *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 46, No. 5, May 2008.
6. S. Prasad, L.M. Bruce, "Multiple Kernel Discriminant Analysis and Decision Fusion for Robust Sub-pixel Hyperspectral Target Recognition," in *Proceedings of IEEE Geoscience and Remote Sensing Symposium*, Boston, MA, July 2008.
7. T. West, L. M. Bruce, "Multiclassifiers and Decision Fusion in the Wavelet Domain for Exploitation of Hyperspectral Data", *Proc. IEEE Geoscience and Remote Sensing Symposium (IGARSS)*, Barcelona, Spain, July 2007.
8. T. West, L. M. Bruce, S. Prasad, "Wavelet Packet Tree Pruning Metrics for Hyperspectral Feature Extraction", *Proc. IEEE Geoscience and Remote Sensing Symposium (IGARSS)*, Boston, Massachusetts, July 2008.
9. Analytical Spectral Devices Fieldspec Pro Spectroradiometer specifications. Available on line at http://asdi.com/products_specificationsFSP.asp
10. SpecTIR Airborne Hyperspectral Remotely Sensed Imagery specifications. Available on line at http://www.spectir.com/srs.htm